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Physics-inspired Metaheuristics for Construction Site Layout Planning Problem

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Abstract

In the construction industry, material handling plays an important role. Finding proper locations for construction facilities not only can affect the expenses, but also it can impact on the process of handling of construction materials. Therefore, in order to supply engineering demands and materials, the construction site layout planning problem (CSLP) within a short-distance transportation is considered as an NP-hard problem. Thus, the researchers are extensively using metaheuristics in order to solve the construction site layout planning problems. This study presents a comparative study of ten physics-inspired metaheuristics with regard to their efficacy in how they can address a real construction site layout problem. In this vein, two case studies are examined in terms of the site layout planning. Finally, the findings reveal that Gravitational Search Algorithm (GSA) and Thermal Exchange Optimization (TEO) have the ability to come up with better solutions, in comparison to other considered optimization algorithms.

Keywords

construction site layout planning problem, gravitational search algorithm, galactic swarm optimization, big bang-big crunch, quantum-inspired genetic algorithm, electromagnetic field optimization

1 Introduction

In the past few decades, many studies have been conducted so that to figure out the best way of approaching unsolved problems of construction site layout planning is an indispensable part of any given project going on. The location of the different facilities can play a vital role in the performance of site precast yards, in other words, in optimizing the layout of the construction site precast yard [1]. As a result of this, so as to solve the problems related to the site layout; many high-level procedures like metaheuristics have been enormously put into action [2]. Therefore, a well-designed site layout of construction can clearly elevate the efficiency of production. In this regard, the majority of building companies are highly motivated to enjoy having an excellent management and organization so that they can be able to keep up with the global competitive market, to guarantee their productivity, and increase their net income [3]. When it comes to the Construction Site Layout Problems (CSLPs) both providing materials and engineering requirements within a short-distance transportation are very attractive fields of research, mostly because these fields of study have the potential to combine qualities of both the aesthetic and the functional aspects of layout within the process of planning the facility [4].

Material handling, which involves some short-distance movements, plays an crucial role in the construction and manufacturing activities [5]. The expenses and the time of the construction in the material handling system will be extremely affected if the location of facilities be located suitably in the site. According to the research which has been done by Tompkins et al. [6], in most companies, material handling takes a large portion of the total budget between 20 to 50 percent. Moreover, having properly-positioned facilities can considerably cut these costs around 10–30% at the minimum [6]. It is worth bringing in mind that 36% of the increasing costs in material handling can be just the results of having an ineffective-layout [7].

The construction site layout planning (CSLP), as an important problem, which is known as a Quadratic Assignment Problem (QAP), and is an NP-hard Problem [8]. This problem is associated with the movement of materials between facilities. Having ample construction space is a necessity for any construction project, for it needed for a range of short-term facilities; well-functioning, and safe, construction movements. One of the main steps in planning the site is construction site-level facilities layout [5]. Organizing a set of work space in the construction site that

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can provide a level of safety and efficiency is not a simple task, but rather a multifaceted job to do, because it inevitably involves a lot of scenarios that should be taken into consideration.

In the last few years, researchers have constantly been trying to tackle the problem of construction site layout through applying metaheuristic algorithms. In this regard, it is worth mentioning that there are a plethora of metaheuristic algorithms that can solve the construction site layout problem; therefore, this article set out with the aim of comparing the performance of physics-inspired optimization algorithms in terms of optimizing the construction site layout problem. These algorithms include: Big Bang-Big Crunch (BB-BC) [9], Ray Optimization Algorithm (RO) [10], Water Evaporation Optimization (WEO) [11], Thermal Exchange Optimization (TEO) [12], Gravitational Search Algorithm (GSA) [13], Electromagnetism-like Mechanism (EM) [14], Central Force Optimization (CFO) [15], Galactic Swarm Optimization (GSO) [16], Quantum-inspired genetic algorithm (QGA) [17], Electromagnetic Field Optimization (EFO) [18]. Since the performance of ten physics-inspired metaheuristics in solving a real construction site layout problem is compared in this study, which is a large number of algorithms to consider for such a comparison, this study is unique in several aspects. Most of the previous studies have focused on a few algorithms or a single algorithm with different variants. It applies these algorithms to the linear construction site layout planning problem, which is a special case of the quadratic assignment problem that assumes linear costs associated with the flow between facilities. This assumption may be more realistic for some construction projects and may reduce the complexity of the problem. It contributes to the body of existing knowledge by providing an overview of ten physics-inspired metaheuristic algorithms, which are algorithms inspired by non-linear physical phenomena such as gravity, electromagnetism, thermodynamics, etc. These algorithms have shown formidable exploration and exploitation abilities for optimization problems. It also evaluates the effectiveness and efficiency of these algorithms on a set of real-world case studies, and analyzes the strengths and weaknesses of each algorithm. It may provide useful insights and guidelines for practitioners and researchers who are interested in solving the construction site layout planning problem using metaheuristic algorithms.

The rest of the article is organized as follows: The literature review is presented in Section 2. Section 3 presents the optimization algorithms, and Section 4 presents formulations and modeling of the CSLP. Final discussion, Concluding remarks, and future directions are presented in Section 5.

2 Literature review

In this section, a literature review of the Metaheuristic Algorithms and Construction Site Layout Problem will be presented.

2.1 Metaheuristic algorithms

In the last decade, metaheuristic algorithms have gained popularity among researchers in order to find out better solutions for problems that we are facing almost every single day in our life. As a result of this, a variety of metaheuristics – with various attitudes and aspects – are developed, and at the same time they are utilized in virtually all fields. Also, advanced metaheuristic and evolutionary algorithms have been significantly used in solving several complex construction engineering problems such as: reliability assessment of reinforced concrete beams under elevated temperatures [19], optimizing the size and shape of trusses [20, 21], reliability based topology optimization of thermoelastic structures [22], estimating the optimal mixture design of concrete pavements [23], reliability-based numerical analysis of glulam beams [24], optimizing fly ash concrete mixtures [25], and etc. Exploring efficiency is one of the main goals of these optimization methods, which can eventually lead to a global solution. These algorithms are neither problem-specific nor dependent on the objective function, so both industry and academic community are enormously paying attention to this field of knowledge [26].

Having some unique features, such as efficiency and clarity for analyzing natural phenomena, it has brought about some well-known algorithms such as Genetic Algo-rithms [27], according to Darwin's theory of survival of the fittest and Ant Colony Optimization [28] in 1999 based on the behavior of ants. Narayanan and Moore [17] proposed Quantum-Inspired Genetic Algorithm (QGA) in 1995. This can be seen the advent of the optimization algorithms inspired by physics. In this line of thought, that is, quantum mechanics, a wide number of hypotheses and ideas began to spawn. In 2003, Birbil and Fang [14] offered Electromagnetism-like (EM) mechanism on the ground of the superposition rules of electromagnetism. Big Bang–Big Crunch (BB-BC) [9] was presented in 2005, which was inspired by the theory of destruction and creation of the universe. Moreover, some other algorithms came out, for example, Central Force Optimization which was inspired by Newton's gravitational law and laws of motion algorithms [15] by Formato in 2007, and also, Gravitational Search Algorithm by Rashedi et al. [13]. Kaveh and Khayatazad [10] proposed Ray Optimization algorithm (RO) in 2014 based on Snell's light refraction law. Abedinpourshotorban et al. [18] proposed electromagnetic field optimization based on various electromagnets with different polarities 2016. In 2016 Galactic Swarm Optimization was presented by Muthiah-Nakarajan and Noel [16] and Water Evaporation Optimization [11] was suggested by Kaveh and Bakhshpoori. Most recently in 2017, Kaveh and Dadras [12] presented thermal exchange optimization on the grounds of Newton's law of cooling.

2.2 Construction Site Layout Planning (CSLP)

The formulation of the construction site layout planning (CSLP) problem is mostly about the location of a variety of facilities in particular spots inside the site borders, and at the same time, optimizing layout objectives and meeting the limitations of that layout. Unarguably, having an optimal construction site layout can significantly reduce the transportation time and overall costs, and what's more, it can escalate the productivity and create a safe working environment. The CSLP problem or in other words assigning a number of predetermined facilities n, optimally to a number of predetermined unoccupied locations m, where $m \geq n$. Generally speaking, the CSLP problem can be modeled either as a facility to site assignment or a facility to location assignment [29]. The first assigns a set of predefined facilities to a set of predefined locations on site. The method of facility to site assignment, in contrast, assigns a set of predefined facilities to any available space which is unoccupied on site and results in a more complicated formulation, since several spatial restrictions must be satisfied at the same time. Whether all facilities can fit to every possible location or not is a deciding factor in both problem forms, because it. The CSLP problem can be told apart as a dynamic or a static one which highly relates to whether non-changing or changing site facilities and site spaces are taken into account in various project phases. CSLPs are known as combinatorial optimization problems. In this vein, there are two approaches including metaheuristics, especially, when it comes to large search sized problems, and also, the exact approach requires, with a global search, for smaller search sized problems [30]. Selecting each of these algorithms relies on many a factor such as the quality of the solution, computational time, interaction of parameters, complexity, and behavior of the algorithm, in particular the analysis of larger problems. Different search algorithms have been used in solving CSLPs. Yeh [31] presented the application of annealed neural networks, Li and Love [32] applied the Genetic Algorithm (GA) to find the optimal solution in a site-level unequal-area facility layout problems. Therefore, Li and Love [33], who had this presumption that predetermined locations are both rectangular shape and satisfactorily sufficiently large to embed the biggest facility, to solve the CSLP they used the genetic algorithm. In addition, Gharaie et al. [34] by applying ant colony optimization found a solution for their model. Mawdesley and Al-Jibouri [35] proposed a sequence-based genetic formulation of the CSLP problem. They estimated its performance through comparing its findings with that of Yeh [31]. A joined max-min ant system, in other words MMAS, and GA model was suggested by Lam et al. [36] in which MMAS is applied to develop the initial population for the GA application. What's more, in order to handle a site pre-cast yard layout problem, Cheung et al. [37] proposed utilizing the GA software Evolver. Moreover, a multi-searching tabu search tabu search procedure by Liang and Chao [38] which relied on efficient diversification and intensification methods to properly enhance the different arrangements in the facility layout problem. Lam et al. [36] applied an Ant Colony Optimization (ACO) algorithm to solve the CSLP problem where the proximity of the facilities was calculated by the application of entropy technique and fuzzy reasoning. To lay out the pre-cast facilities in the construction site, Wong et al. [1] elaborate upon a GA and a mixed integer programming (MIP) model to produce optimal layout solutions. Gholizadeh et al. [39] carried out a harmony search algorithm as an alternative tool for the solution of the CSLP problem. In this line of thought, a Particle Swarm Optimization (PSO) was proposed by Zhang and Wang [40] for an unequal area static CSLP problem, formulated as a quadratic assignment problem (QAP).

3 Optimization algorithms

3.1 Big Bang-Big Crunch (BB-BC)

The Big Bang–Big Crunch (BB–BC) [9] algorithm is inspired mainly from the expansion phenomenon of Big Bang and shrinking phenomenon of Big Crunch. This is a commonly held belief that the Big Bang is the theory of the advent of the universe. As far as this theory is concerned about space, time, energy, and matter that at one time all of them in the universe were squeezed into a minuscule volume, then a tremendous explosion happened leading to the creation of our universe. After that until now, the universe is constantly expanding. Generally speaking, this expansion of the universe is because of Big Bang. Many scientists, on the other hand, hold this view that this expansion will not continue for good, and as a result of which, all matters would fall down into the largest black hole which pulls everything within it, which is called as Big Crunch.

There are two conspicuous phases in BB-BC algorithm, namely, Big Crunch phase and Big Bang phase. Firstly, during Big Crunch phase, the center of mass will be computed resembling black hole (gravitational attraction). Secondly, during Big Bang phase, the center of mass will be computed resembling black hole (gravitational attraction). Big Bang phase makes sure the exploration of solution space. Big Crunch phase accomplishes the necessary exploitation and convergence, as well.

BB-BC algorithm suffers from botching all candidates into a local optimum. Should a candidate with the best fitness value converge to an optima at the starting point of the algorithm, as a result of which, all remaining candidates will follow that best answer and be trapped into local optima. This happens on the ground that the initial population is not uniformly dispersed in the solution space. Therefore, this algorithm makes a methodology available to obtain uniform initial population in BB-BC [9].

The algorithm named as Big Bang-Big Crunch (BB-BC) is taken from the prevailing evolutionary theory for the origin of the universe: the Big Bang Theory. As far as this theory is concerned, in the Big Bang phase, particles are drawn toward irregularity by losing energy, while in the Big Crunch phase, they converge toward a particular direction. BB-BC begins the same way as other population based metaheuristics do; it commences with a set of random initial candidate answers, as the initial Big Bang. To be more specific, every Big Bang phase will be followed in advance of a Big Crunch phase, but the first population is an exception because it should be produced randomly within the search space. A Big Crunch phase - after each Big Bang phase - for determining a convergence operator should take place, because in this way particles will be drawn into an orderly fashion in the following Big Bang phase. The convergence operator can be the weighted average of the positions of the best candidate solution or the position of the candidate solutions. These two contraction (Big Crunch) and dispersing (Big Bang) phases are occurred several times in the cyclic body of the algorithm in succession to meet the expectation of a stopping criteria with the aim of steering the particles toward the global optimum [9].

3.2 Ray Optimization Algorithm (RO)

The fundamental notion behind the RO is based on Snell's law which is the refraction of light. According to this approach, every solution vector is simulated by a light ray which moves in the space. The direction of movement of a light ray is altered when it passes from a lighter medium to a darker medium. Thanks to this occurrence, one can lead the solution vector to a global or near-global optimum solution [10].

In this regard, like other multi-agent methods, the Ray Optimization (RO) algorithm proposed by Kaveh and Khayatazad [10] has several particles which constitute the variable of the problem. These agents are defined as rays of light. When light travels from a lighter medium to a darker one – based on the Snell's light refraction law – its direction is altered and it also reflects. This behavior assists the agents to scrutinize the search space in early stages of the optimization process and to lay the foundation for them to converge in the final stages.

According to Snell's light refraction law, light reflects when it travels from one medium to another. The refraction relies on (1) the refraction index ratio of two mediums and (2) the angle between the incident ray and the normal vector of the interface surface of two mediums. When it goes across from a lighter medium to a darker one, through the alteration of its direction, it gets closer to the normal vector. This physical behavior is the foundation of the RO. The agents of RO are regarded as starting points of rays of light that are updated in the search space or that travel from one medium to another one based on Snell's light refraction law. Clearly, since each ray of light is a vector, its direction and length is the searching step size in the current iteration, its commencing point is the previous position of the agent in the search space, and its end point is the current position of the agent achieved by adding the step size to the starting point. The refraction vector is obtainable based on Snell's law as the new searching step size by taking into account an effective vector as the normal vector of the interface surface between two mediums and an effective value for the refraction index ratio of two mediums. Subsequently, the new position of agents will be updated points to explore the search space and converge to the global or near-global optimum. The current position of the agents as both ending and starting points of this vector is necessary to utilize the Snell's law. Nevertheless, the other one should be selected in such a way that it yields a well balance between exploration and exploitation. RO considered efficaciously the normal vector in order to start from a point determined based on the individual and collective information of agents and end at the current position of agents. RO begins from a random initial search step sizes and a randomly generated initial candidate solutions. These are the rays of light that travel from one medium to another in the cyclic body of the algorithm. In actuality, RO set out with the aim of enhancing the quality of the offered solutions by refracting the rays toward the promising points acquired according to the well-known solution by each agent and all of them [10].

3.3 Water Evaporation Optimization Algorithm (WEO)

The inspiration source of the idea of Kaveh and Bakhshpoori [11] was the evaporation of a small amount of water molecules on the solid surface with different wettability which can be examined by molecular dynamic simulations. According to the molecular dynamic simulations, it is common knowledge that, when the surface is altered from hydrophobicity to hydrophility, the evaporation speed will not bring about any sign of a monotonically reducing from intuition, but rather, escalate first and then decrease after meeting a maximum value. By the time that the surface wettability of the substrate is not high enough, the water molecules collect into the form of a sessile spherical cap. The crucial factor that influences the evaporation speed is the geometry shape of the water aggregation. At the same time, when the surface wettability of the substrate is high enough, the water molecules spread to a monolayer, and the geometric factor has no influence anymore, and the obstacles of energy which are supplied by the substrate instead of the geometry shape influence the evaporation speed. WEO considers water molecules as algorithm individuals. Solid surface or substrate with variable wettability is shown as the search space. Reducing the surface wettability, that is, the substrate changing from hydrophility to hydrophobicity, makes changes in the water aggregation from a monolayer to a sessile droplet. The very reaction is aligned with the way layout of individuals alters to each other as the algorithm develops. Reducing wettability of the surface can show the reduction of objective function for a minimizing optimization problem. For having up-to-date individuals in which its pattern of change is compatible with the global and local search ability of the algorithm, and also can assist WEO having remarkably well converged behavior and simple algorithmic structure, evaporation flux rate of the water molecules can be seen as the best suitable measure [11].

3.4 Thermal Exchange Optimization Algorithm (TEO)

Kaveh and Dadras [12] proposed a novel metaheuristic named Thermal Exchange Optimization (TEO) algorithm, which was based on Newton's law of cooling. Newton's law of cooling holds this view that the rate of heat loss of a body is proportional to the difference in temperatures between the body and its surroundings. TEO takes into account each of its particles as a heating or cooling object, and by incorporating another agent as the environment, a heat transferring and thermal exchange occurs between them. The new temperature of the object is considered as its next position in the search space.

TEO begins from a set of randomly generated initial candidate solutions, the same as other metaheuristics do. In every iteration of the algorithm, all agents of the population are evaluated and sorted according to their objective function values. Afterwards, the population is categorized into two sections with the same number of objects. Regardless of which group objects belong to, all of them will be affected by the environmental temperature. In this regard, should the object belong to the first half, its environmental temperature will be its corresponding object from the second part and the other way around. The best results are the objects from the first half; they have higher temperatures that are cooled by moving a little bit toward the particles with a lower temperature. The bad particles, from the objects from the second half and have low temperature, are heated by moving toward the particles with higher temperature. The heat transferring between the objects happens in the cyclic body of the algorithm in order to conduct all particles to the better positions without any variance in the temperature. It is worth mentioning that TEO takes advantage of having a memory with a particular size for saving the best-so-far known solutions. TEO used these memorized particles in order to replace a similar number of worst ones in each of its iterations [12].

3.5 Gravitational Search Algorithm (GSA)

The concept of gravitational search algorithm (GSA) lies behind the law of gravity and the idea of mass interactions [13]. The GSA applies the theory of Newtonian physics and its searcher agents are the collection of masses. In GSA, there is an isolated system of masses which applies the gravitational force, every mass in the system can find the location of other masses. Thus, the gravitational force can be seen as a tool for transferring information between various masses. The GSA agents can be defined as objects; additionally, their performance is measured by their masses. All these objects attract each other by a gravity force, and this force brings about a movement of all objects globally toward the objects with heavy masses. The heavy masses correspond to better solutions of the problem. Moreover, the position of the agent corresponds to a solution of the problem, and its mass is determined using a fitness function [13].

3.6 Electromagnetism-like Mechanism (EM)

The superposition principle of electromagnetism is the main source of EM [14] algorithm, which asserts that the force applied on a point by other points is inversely proportional to the distance between the points and directly proportional to the product of their charges. Points in solution space are considered as particles. The charge of each point is computed in accordance with their objective function value. As far as classical physics is concerned, the charge of a particle generally remains the same, but in this heuristic the charge of each point is not constant, but rather, it changes from one iteration to another [14].

3.7 Central Force Optimization (CFO)

CFO [15] is based on the theory of particle kinematics in gravitational field. Newton's universal law of gravitation indicates that larger particles will have more attraction power, in comparison with smaller particles. Therefore, smaller ones will be attracted towards the larger ones. With this in mind, subsequently, all smaller particles will be attracted towards the largest particle. This largest particle can be resembled as the global optimum solution in case of optimization. To replicate this idea in CFO, a set of solutions is taken into account as probes on the solution space. Each probe will undergo gravitational attraction due to the other probes [15].

3.8 Galactic Swarm Optimization (GSO)

Recently, Galactic swarm optimization (GSO) introduced a metaheuristic based on the idea of stars and galaxies in the universe. Because this algorithm applies multiple exploitation and exploration cycles, it paves the way for finding the global optimum with the maximum accuracy. The original galactic swarm optimization algorithm simulates the motion of stars and galaxies in the universe. Since the stars are not distributed in equal numbers in the cosmos, they are concentrated in galaxies and as a result they are not evenly distributed. The attraction of the stars and galaxies in the GSO algorithm is mimicked in the following way [16].

First, the initial population is categorized into subpopulations which are called sub-swarms; all the individuals of the sub-swarms begin their motion as stated by the PSO algorithm with a specific number of iterations, and all the individuals in each subpopulation will be attracted towards the individual with better fitness; thus, at the end of the iterations each of the subpopulations will be displaced by the best individual of each of the subpopulations.

The best individuals of all the subpopulations will pass into a second phase, where they will form a new super swarm, and (in the same way they will move according to the PSO algorithm at the end of the iterations) the GSO algorithm will return us the best individual of the super swarm which will represent the best solution found in the entire initial population [16].

3.9 Quantum-inspired Genetic Algorithm (QGA)

As stated by quantum mechanics, an orbit is defined when an electron is moving around the nucleus in an arc path. In this line of thought, electrons are located in different orbits, which depend on the energy level and angular momentum. An electron in lower level orbit can jump to higher level orbit by taking in a certain amount of energy; similarly a higher level electron can jump to lower energy level by releasing a certain amount of energy. This type of jumping is known as discrete. There is no intermediate state in between two energy levels. The position where an electron lies on the orbit is uncertain, it is a possibility of being situated at any position in orbit at a particular time. The unpredictability of the electron's position is also referred to as the superposition of the electron [17].

As stated by classical computing, a bit is represented either by 0 or 1. In quantum computing, on the other hand, this is named as qubit. The state of a qubit can be 0 or 1 or both at the same time in superposition state. This superposition of qubit emulates the superposition of particles or electrons. The state of qubit at any specific time is defined by probabilistic amplitudes. The location of an electron is represented with regard to qubits by a vector named quantum state vector.

QGA [17] utilized the concept of parallel universe in Genetic Algorithm (GA) to mimic quantum computing. As far as this parallel universe interpretation is concerned, each universe carries its own version of population. All populations go after the same rules, but one universe can interfere in the population of other universe. This interference happens as in the shape of a different kind of crossover named interference crossover, which paves the way for having good exploration capability to the algorithm. In QGA, all the solutions are encoded using superposition, and what's more, all of these solutions may not be authentic, which causes difficulties during the execution of crossover [17].

3.10 Electromagnetic Field Optimization (EFO)

In 2016, Abedinpourshotorban et al. [18] presented a creative metaheuristic intelligent algorithm named Electromagnetic Field Optimization. While the swarm-based metaheuristic algorithms are widely inspired by biology, on the other hand, the EFO algorithm is inspired by the electromagnetic field law used in physics. In the EFO algorithm, because of the forces of attraction and repulsion in the electromagnetic field, the electromagnetic particle (EMP) stays away from the worst solution and tries to find the best solution. Finally, all the electromagnetic particles (EMPs) gather around the optimal solution.

A magnetic field is produced around the electrified iron core, which is made of an electromagnet. An electromagnet has only one polarity and it is dependent on the direction of the electric current. Subsequently, an electromagnet has two features of repulsion or attraction, electromagnets with different polarity attract each other, and those with similar polarity repel each other. The intensity of attraction is 5–10% higher than repulsion; moreover, the ratio between attraction and repulsion is set as golden ratio [18], which can improve the algorithm to search for the optimal solution successfully in the search space. The main idea of the optimization problem has to do with finding the pole (maximum or minimum) of the corresponding fitness in the prescribed range and the objective function [18]. Each possible solution of the problem is represented with an electromagnetic particle consisting of a number of electromagnets. The electromagnetic field comprises many electromagnetic particles and it can be described a space in 1-D (dimension), 2-D, 3-D, or hyperdimensional space [18]. The number of electromagnets of an electromagnetic particle corresponds to variables of the optimization problem, along with the dimension of the electromagnetic space. In addition, all electromagnets of one electromagnetic particle have similar polarity. As a result of which an electromagnetic particle has the same polarity with its electromagnets.

4 Site layout planning test problems and optimization results

It goes without saying that the construction site layout problem was formulated as a QAP. At first, Koopmans and Beckmann [41] proposed a formulation which was dealing with individual locations, to put it differently, assigning facilities to locations. Furthermore, this basic hypothesis is like the foundation for the layout problem that each facility occupies precisely the same amount of area as other facilities do; therefore, there is no difference that what facility is assigned to what site [41]. Based on this fact that the construction site layout problems are a permutation problems, by altering of the continuous-based initial solution vectors into the permutation vector by applying the indices that would sort the corresponding initial solution vector (see Table 1).

The results and analysis of the algorithms after 30 independent runs (to remove their inherent randomness) on each of the cases are presented below. The total number of times that the objective function was called from each algorithm was kept equal so that the performance of the algorithms can be measured correctly.

4.1 Site-level facilities layout problem

This problem tries to find the most suitable arrangement for placing a set of predetermined facilities into a set of predetermined spaces on the site. Moreover, this problem is based on this hypothesis that every predetermined place is capable of accommodating the largest one among the facilities. The goal of site-level facility layout has to do with minimizing the overall traveling distance of site personnel between facilities. Let δ_{ik} be a binary variable that indicates whether facility i is located at location k ($\delta_{ik} = 1$) or not ($\delta_{ik} = 0$). Similarly, let δ_{jk} be a binary variable that indicates whether facility j is located at site l ($\delta_{jk} = 1$) or not ($\delta_{jk} = 0$). Let f_{ij} be the number of daily trips between facilities i and j by construction workers. Let d_{kl} be the distance between sites k and l. Then, TD is the total daily distance traveled by construction workers, given by the Eq. (1) and subject to Eq. (2):

$$Minimize\ TD = \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{l=1}^{N}\sum_{k=1}^{N}\delta_{ik}\delta_{jl} f_{ij} d_{kl} \quad (1)$$

Table 1 Solution vector representation

Locations	1	2	3	4	5	6	7	8	9
Facilities (Initial solution vector)	0.33	0.92	0.25	0.23	0.79	0.04	0.1	0.74	0.69
Facilities (Modified solution vector)	5	9	4	3	8	1	2	7	6

$$Subject\ to: \begin{array}{l} \sum_{i=1}^{N} \delta_{ij} = 1 \\ \sum_{j=1}^{N} \delta_{ij} = 1 \end{array} \quad (2)$$

The distance is represented as the length between centers of the two locations if the two locations are beside each other; if not, it is the sum of segmental distances between the two locations. For instance, d_{ik} is the sum of d_{mj} and d_{jk} If there are two paths linking the two locations, then the shorter path is chose for calculating the distance [32].

The number of predetermined places should be equal to or greater than the number of predetermined facilities. A number of dummy (fictitious) facilities will be added to make both numbers equal when the number of predetermined places is greater than the number of predetermined facilities. By allocating both frequency and the distance as 0, the dummy facilities will not influence the layout results.

The performance of ten physics inspired metaheuristics in solving Site-level facilities layout problem are investigated by a case study from Li and Love [32]. In situations like this, there are 11 facilities to be allocated to 11 locations with predetermined geometric positions on site. As can be seen in Table A1, there are the 11 facilities and their corresponding index numbers. The travel distance between predetermined locations is measured and presented in Table A2. Trip frequency between facilities influences site layout planning. Thus, the frequencies of trips made between facilities in one day are shown in Table A3.

This case was solved by accomplishing 30 independent optimization runs through 200 iterations to achieve statistically significant findings by the investigated algorithms. Statistical results of 30 independent runs are compared in Table 2. According to Table 2, the average, worst and standard deviation for GSA are 12,555, 12,612 and 26.81, respectively, which are better than other metaheuristics. This not only will shows that GSA comes up with a better best solution ,but it also is more stable. Having a close competition, the TEO shows better results than other solution methods. The average, worst and standard deviation for TEO are 12,556, 12,654 and 31.16, respectively. The mean convergence curves for all algorithms with regard to the number of iterations are shown in Fig. 1. A comparison of the results of all metaheuristics for this case is shown in Table 3. The findings present that in this example the best answer is 12,538 which is better than previous studies and all the studied metaheuristics are able to find this solution.

Table 2 Comparison of the results of 30 independent runs for the first case example

Algorithm	Best	Average	Worst	STD
PSO	12546	12,560	12756	47.39
CBO	12546	12558	12768	45.51
ECBO	12546	12555	12746	32.11
BB-BC*	12538	12581	12678	39.46
RO*	12538	12602	12746	91.52
WEO*	12538	12588	12756	89.96
TEO*	12538	12556	12654	31.16
GSA*	12538	12555	12612	26.81
EM*	12538	12664	12768	103.04
CFO*	12538	12606	12768	97.35
GSO*	12538	12599	12756	90.50
QGA*	12538	12569	12746	60.83
EFO*	12538	12575	12678	37.73

* Present work

4.2 Site precast yard layout planning problem

A site precast yard layout planning optimization model, which has been proposed by Cheung et al. [37], and many methods were applied to solve the model [1, 4, 30, 38, 42]. The following explanations, which are derived from the model of Cheung et al. [37], try to clarify the definition of the site pre-cast yard layout arrangement optimization problem.

- The spatial arrangement of available locations is unchangeable.
- One location for only one facility at a time
- Equality between the number of locations and the number of facilities (substitute facilities can be added for computation purposes if numbers of facilities are fewer than the number of places)

In the Cheung's model, n locations are occupied by n facilities. As far as the repetition of traveling and the description of distance are concerned, the facilities are located in their suitable locations; also, different kinds of resources will be taken into account so that the expenses of transportation between facilities could be measured properly. Thus, the layout planning can meet its final goal, which is obtaining the lowest transportation of resources to facilities by having a well-arranged site. According to the goal of a function in the site, any replacement facilities with each other can increase the total cost or bring it down. The total cost is defined as follows:

$$minimize\ Total\ \ \mathrm{Cos}t = \sum\nolimits_k^n \sum\nolimits_i^n \sum\nolimits_j^n TCL_{Mk\ i,j}\ , \quad (3)$$

where $TCL_{Mk\ i,j}$ calculates by Eq. (4):

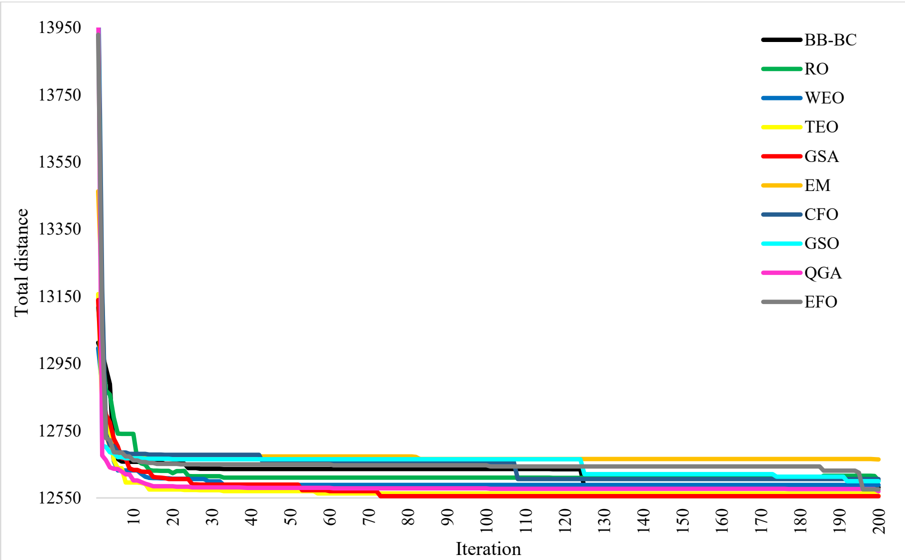

Fig. 1 Mean convergence history of the proposed physics-inspired metaheuristic algorithms

Table 3 Comparison of the best solution of algorithms

Algorithms	Total distance	Best layout										
		F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
PSO [4]	12,546	9	11	5	6	7	4	3	1	2	8	10
CBO [4]	12,546	9	11	6	5	7	4	3	1	2	11	4
ECBO [4]	12,546	9	11	4	5	7	6	3	1	2	8	10
GA [32]	15,090	11	5	8	7	2	9	3	1	6	4	10
ACO [34]	12,546	9	11	6	5	7	2	4	1	3	8	10
BB-BC*	12,538	9	11	5	6	7	2	4	1	3	8	10
RO*	12,538	9	11	5	6	7	2	4	1	3	8	10
WEO*	12,538	9	11	5	6	7	2	4	1	3	8	10
TEO*	12,538	9	11	5	6	7	2	4	1	3	8	10
GSA*	12,538	9	11	5	6	7	2	4	1	3	8	10
EM*	12,538	9	11	5	6	7	2	4	1	3	8	10
CFO*	12,538	9	11	5	6	7	2	4	1	3	8	10
GSO*	12,538	9	11	5	6	7	2	4	1	3	8	10
QGA*	12,538	9	11	5	6	7	2	4	1	3	8	10
EFO*	12,538	9	11	5	6	7	2	4	1	3	8	10

* Present work

$$TCL_{Mk\ i,j} = M_{LM\ i,j} \times C_{Mk}\ . \tag{4}$$

C_{Mk} shows cost per unit distance according to resources *Mk* flow. $M_{LM\,i,j}$ defines the distance moved of resource *Mk* flow per unit time between locations *i* and location *j* which will be computed by Eq. (5):

$$M_{LM\ i,j} = FL_{Mk\ i,j} \times D_{ij}\ . \tag{5}$$

The sign of $FL_{LM\,i,j}$ shows the frequency of resource *Mk* flow from and to between location *i* and *j*, per unit time. These calculations use Eq. (6). Also, D_{ij} means the distance between location *i* and *j*, which will be computed by Eq. (7):

$$FL_{Mk\ i,j} = \begin{bmatrix} FL_{Mk\ 1,1} & FL_{Mk\ 1,2} & \cdots & FL_{Mk\ 1,q} \\ FL_{Mk\ 2,1} & FL_{Mk\ 2,2} & & FL_{Mk\ 2,q} \\ \vdots & & \ddots & \vdots \\ FL_{Mk\ q,1} & FL_{Mk\ q,2} & \cdots & FL_{Mk\ q,q} \end{bmatrix}, \tag{6}$$

$$D_{i,j} = \left|XL_j - XL_i\right| + \left|YL_j - YL_i\right|, \tag{7}$$

wherever we see L_i and L_j it means that they are the coordinates of the locations within the site area.

There are 11 predetermined locations in the yard that require to have 11 allocated facilities. In this regard, in Table A4 the facilities and their corresponding index numbers are listed. Moreover, Table A5 shows four types of resources and transport costs per unit distance. Coordinates of the available locations are shown in Table A6. By having these coordinates, the rectangular distance matrix D_{ij} for the locations was then calculated and displayed as Table A7. Flow frequency of the four types of resources between the facilities are listed in Table A8.

Because of the central limit theorem, the sample size must be equal or more than 30. If the sample size gets larger, then the distribution of the sample mean converges to the normal distribution; therefore, 30 independent experimental runs through 1000 iterations are performed. By applying ten optimization methods, the problem is solved by MATLAB R2017a. In this vein, we can see a list in Table 4 which is about the analogous results of algorithms for CSLP . The mean convergence curves of algorithms are presented in Fig. 2. Additionally, the comparison of best results of this study and preceding studies have been provided in Table 5.

According to Table 4 and Fig. 2, clearly, the TEO algorithm converges faster than other algorithms with a higher-level of efficiency in the mean (97071) and worst (103020) costs, and the standard deviation of the VPS (2773.7) is better, in comparison with other algorithms. All in all, the Enhanced Colliding Bodies Optimization (ECBO) still performs better solutions for this problem [4].

Table 5 shows that facilities 1 through 11 are closest to locations 5, 7, 9, 6, 1, 10, 8, 3, 11, 2, and 4, respectively.

Table 4 The comparison of algorithms for the CSLP

Algorithm	Best Cost	Mean Cost	Std. Dev.	Worst Cost
GA [40]	99788	N/A	N/A	N/A
MIP [1]	59828	N/A	N/A	N/A
TS [41]	94858	N/A	N/A	N/A
HMCSS+LS [42]	92758	N/A	N/A	N/A
PSO [4]	92758	97667	3363.1	106630
CBO [4]	92758	97504	3149	103038
ECBO [4]	92758	**96670**	2733.5	**102920**
CSS [30]	92758	98074.5	3055	105046
WOA [30]	92758	104189	4677.2	111816
VPS [30]	92758	97301.9	**2498.2**	102308
EVPS [30]	92758	97178.8	2736.4	103502
BB-BC*	92758	100411.4	3311.2	107574
RO*	92758	101428.1	3702.9	107836
WEO*	92758	98147.1	3284.9	105826
TEO*	92758	97071.1	2773.7	103020
GSA*	92758	97111	3019.0	103020
EM*	92758	102905.5	3968.3	107958
CFO*	92758	103144.3	4097.2	108710
GSO*	92758	100827.4	5576.6	109632
QGA*	92758	97432.5	3774.0	105598
EFO*	92758	98817.9	3378.5	107238

N/A: Not available; *Present work

These outcomes are similar to those achieved by Kaveh et al. [4]. The proposed layout arrangement plan and flow diagram for the site pre-cast yard are presented in Fig. 3.

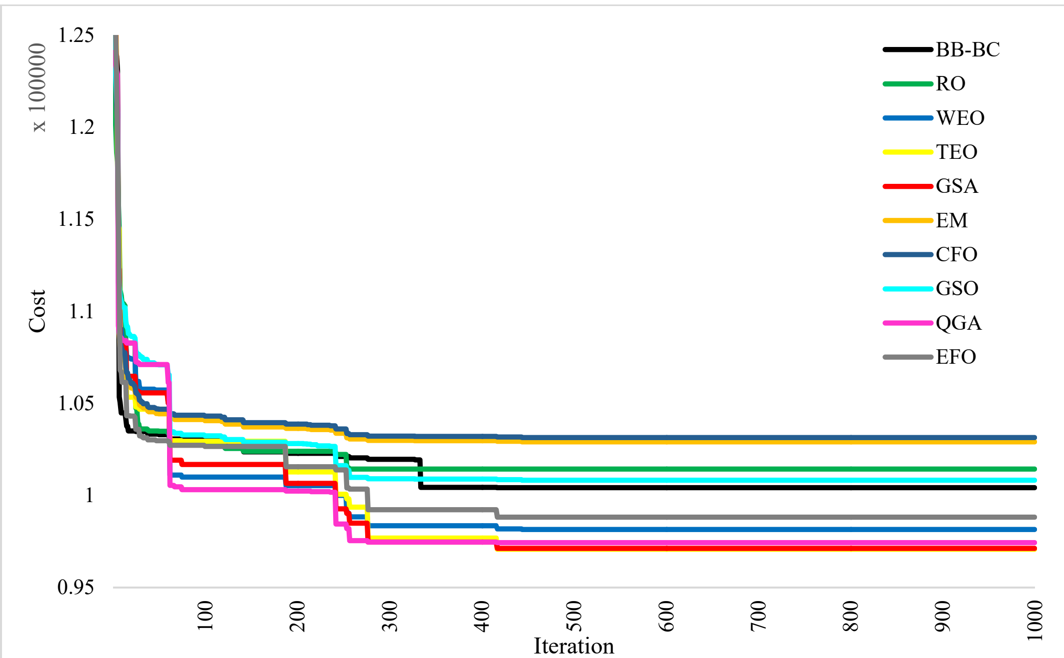

Fig. 2 The mean convergence curves for the CSLP problem obtained by proposed physics-inspired metaheuristic algorithms

Table 5 Best layouts of this paper and previous researches

Algorithm	Best Cost	Best layout										
		F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11
GA [40]	99788	1	10	9	6	8	5	11	3	7	4	2
MIP [1]	59828	1	10	8	6	7	5	9	3	11	4	2
TS [41]	94858	5	7	10	8	1	9	6	3	11	2	4
HMCSS+LS [42]	92758	5	7	9	6	1	10	8	3	11	2	4
PSO [4]	92758	5	7	9	6	1	10	8	3	11	2	4
CBO [4]	92758	5	7	9	6	1	10	8	3	11	2	4
ECBO [4]	92758	5	7	9	6	1	10	8	3	11	2	4
CSS [30]	92758	5	7	9	6	1	10	8	3	11	2	4
WOA [30]	92758	5	7	9	6	1	10	8	3	11	2	4
VPS [30]	92758	5	7	9	6	1	10	8	3	11	2	4
EVPS [30]	92758	5	7	9	6	1	10	8	3	11	2	4
BB-BC*	92758	5	7	9	6	1	10	8	3	11	2	4
RO*	92758	5	7	9	6	1	10	8	3	11	2	4
WEO*	92758	5	7	9	6	1	10	8	3	11	2	4
TEO*	92758	5	7	9	6	1	10	8	3	11	2	4
GSA*	92758	5	7	9	6	1	10	8	3	11	2	4
EM*	92758	5	7	9	6	1	10	8	3	11	2	4
CFO*	92758	5	7	9	6	1	10	8	3	11	2	4
GSO*	92758	5	7	9	6	1	10	8	3	11	2	4
QGA*	92758	5	7	9	6	1	10	8	3	11	2	4
EFO*	92758	5	7	9	6	1	10	8	3	11	2	4

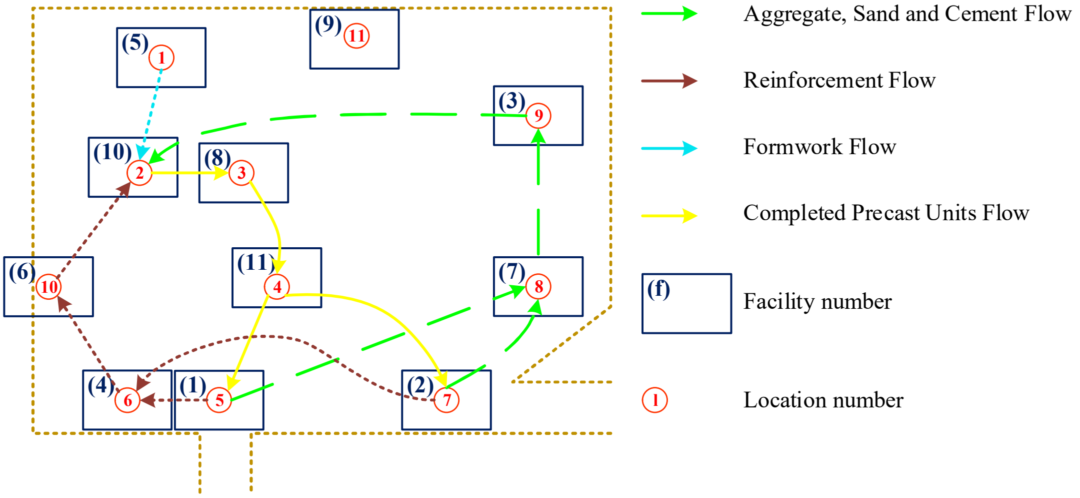

Fig. 3 Proposed layout arrangement plan for the site pre-cast yard

4.3 Construction-site layout planning problem

Along with satisfying the layout restrictions, or constraints, and optimizing the layout objectives, a set of facilities requires to be situated on the site. This model addresses some issues such as the calculated cost of adjacency and distance of objects; additionally, it considers of space availability for object location, and what's more, the location and view of an object in relation to other objects. The feasibility of the layout is calculated as constraints, i.e., each location should be allocated with only one facility, and each facility should be assigned to one location only. The problem is adapted from [31] and [35]. Therefore, the site layout problem is formulated as follows:

$$minimize\ F = \sum_{x}\sum_{i}\delta_{xi}C_{xi} + \sum_{x}\sum_{i}\sum_{y}\sum_{j}\delta_{xi}\delta_{yi}A_{xi}D_{xy}, \quad (8)$$

subject to:

$$\delta_{yj} = 0 \quad if \quad \delta_{xi} = 1 \quad and \quad y \neq x\,, \tag{9}$$

$$\delta_{xj} = 1 \quad if \quad \delta_{xi} = 1 \quad and \quad j \neq i\,. \tag{10}$$

δ_{xi} is the permutation matrix variable (if facility x is assigned to location i) where F is the cost function; C_{xi} is the construction cost of assigning facility x to location i; A_{ij} = 1 if location i is adjacent to location j; D_{xj} is the interactive cost of assigning facility x to the location adjacent to facility y.

For comparing the performance of the ten algorithms, a benchmark case was taken from Mawdesley and Al-Jibouri [35]. This case study demonstrates a practical application in construction site layout problem with the aim of reducing the construction cost. The number of locations matches the number of facilities. In order to gain more information about this case study, please refer to Yeh [31]. In the third case, on a site, this is going to construct two permanent buildings. There are 12 available locations where 12 facilities may be placed (names and index names of them are presented in Table A9).

The construction cost matrix (C), site neighboring index matrix (A) and interactive cost matrix (D) (the unit of all costs in the test case is 1,000) are shown in Tables A10–A12, respectively. Table A10 demonstrates that there is a penalty of 100 for positioning facility 1 or 2 at the location 9 and 10. Note that the units of all costs are $1000. The Interactive Cost Matrix (D) and Site Neighboring Index Matrix (A) are shown in Tables A12 and A11, respectively.

Table 6 Comparison of the algorithms for case 3

Algorithm	Average	Worst	Best	STDEV
ANN [31]	114.7	12.2	93	N/A
GA [35]	N/A	N/A	90	N/A
GA [8]	92.0	N/A	90	N/A
PSO [8]	90.6	N/A	90	N/A
ACO [8]	91.2	N/A	90	N/A
BB-BC*	94.0	100	90	2.8
RO*	94.6	103	90	3.5
WEO*	93.1	100	90	2.9
TEO*	92.3	98	90	2.1
GSA*	91.8	99	90	2.2
EM*	94.7	104	90	3.7
CFO*	94.7	104	90	3.6
GSO*	94.2	102	90	3.4
QGA*	94.1	101	90	3.3
EFO*	93.9	100	90	2.8

N/A: Not available; *Present work

The suggested physics-inspired metaheuristic algorithms were employed to solve this example, and the results were compared. A comparison between the results of the optimal designs reported in the literature and the current study is shown in Table 6. According to experiments, the GSA algorithm displayed to be efficient in Case 3. Moreover, Fig. 4 is about comparisons between mean convergence curve of various algorithms. The GSA seems to be a possible candidate for optimization of CSLP,

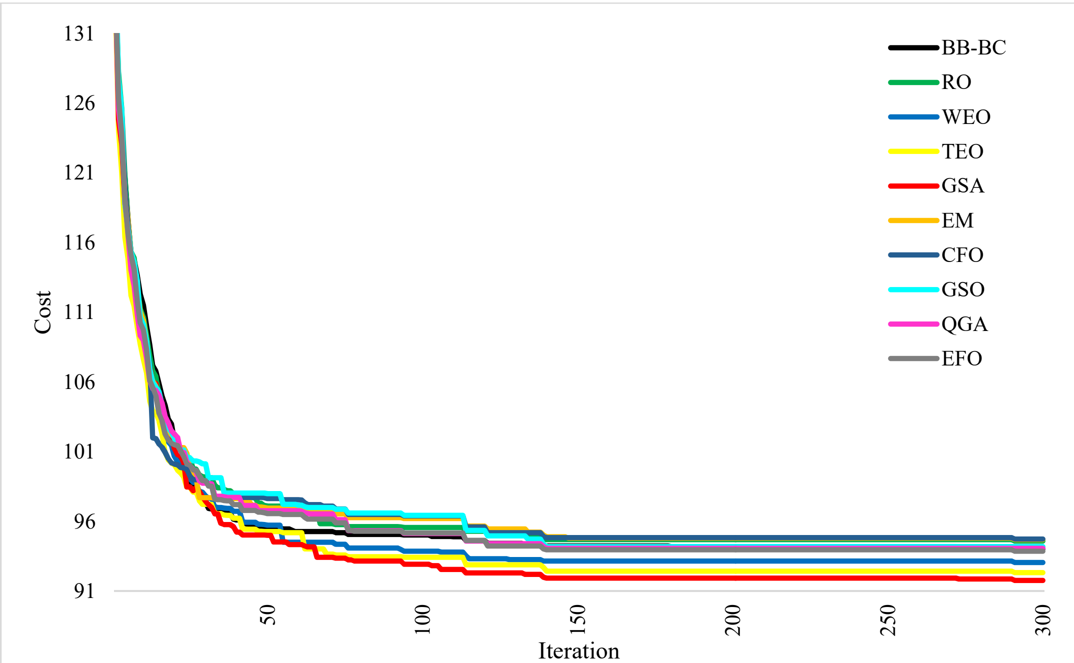

Fig. 4 Mean convergence curve of the algorithms for Case 3

Table 7 Comparison of the Optimal layout solutions of algorithms for Case 3

Algorithm	Best Cost ($1,000)	Best layout											
		F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12
ANN [31]	93	11	12	6	1	7	9	8	10	4	3	2	5
GA [35]	90	9	12	6	10	8	11	7	4	5	2	1	3
GA [8]	90	10	12	9	2	8	11	7	4	5	3	1	6
PSO [8]	90	10	12	9	2	8	11	7	4	5	3	1	6
ACO [8]	90	10	12	9	2	8	11	7	4	5	3	1	6
BB-BC*	90	9	12	6	10	8	11	7	4	5	2	1	3
RO*	90	9	12	6	10	8	11	7	4	5	2	1	3
WEO*	90	9	12	6	10	8	11	7	4	5	2	1	3
TEO*	90	9	12	6	10	8	11	7	4	5	2	1	3
GSA*	90	9	12	6	10	8	11	7	4	5	2	1	3
EM*	90	9	12	6	10	8	11	7	4	5	2	1	3
CFO*	90	9	12	6	10	8	11	7	4	5	2	1	3
GSO*	90	9	12	6	10	8	11	7	4	5	2	1	3
QGA*	90	9	12	6	10	8	11	7	4	5	2	1	3
EFO*	90	9	12	6	10	8	11	7	4	5	2	1	3

mostly because, its convergence in the early stages of the optimization process is fast enough. The best value of objective function in this study was 90 ($1,000).

In Table 7, the best values that algorithms have suggested are listed. All methods that were used are performed equally with regard to efficacy.

5 Final discussion, concluding remarks, and future directions

In this paper, ten physics-inspired metaheuristic algorithms are employed to solve three real construction site layout planning problems. Effectiveness is a criterion by which the performances of these metaheuristic algorithms are compared in this study. According to final results, all of these metaheuristics are capable of reaching the best cost. By investigating the results of experimental studies on mathematical functions and various construction site layout planning problems, it can be found that GSA and TEO perform better than other renowned or new algorithms within the majority of test instances. Since only three benchmark functions have been tested, the lack of research on broader dimensions is the limitation of this research.

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Appendix A

Information of all instances are presented below in tables.

Table A1 Facilities and their corresponding index numbers for case Study 1

Index number	Site facilities	Note
1	Site office	Not fixed
2	False work workshop	Not fixed
3	Labor residence	Not fixed
4	Storeroom 1	Not fixed
5	Storeroom 2	Not fixed
6	Carpentry workshop	Not fixed
7	Reinforcement steel workshop	Not fixed
8	Side gate	Fixed to 1
9	Electrical, water and other utilities control room	Not fixed
10	Concrete batch workshop	Not fixed
11	Main gate	Fixed to 10

Table A2 Travel distance between predetermined locations for Case 1

Distance		Location										
		1	2	3	4	5	6	7	8	9	10	11
Location	1	0	15	25	33	40	42	47	55	35	30	20
	2	15	0	10	18	25	27	32	42	50	45	35
	3	25	10	0	8	15	17	22	32	52	55	45
	4	33	18	8	0	7	9	14	24	44	49	53
	5	40	25	15	7	0	2	7	17	37	42	52
	6	42	27	17	9	2	0	5	15	35	40	50
	7	47	32	22	14	7	5	0	10	30	35	40
	8	55	42	32	24	17	15	10	0	20	25	35
	9	35	50	52	42	37	35	30	20	0	5	15
	10	30	45	55	49	42	40	35	25	5	0	10
	11	20	35	45	53	52	50	40	35	15	10	0

Table A3 Trip frequency between facilities for Case 1

Trip frequency		Facility										
		1	2	3	4	5	6	7	8	9	10	11
Facility	1	0	5	2	2	1	1	4	1	2	9	1
	2	5	0	2	5	1	2	7	8	2	3	8
	3	2	2	0	7	4	4	9	4	5	6	5
	4	2	5	7	0	8	7	8	1	8	5	1
	5	1	1	4	8	0	3	4	1	3	3	6
	6	1	2	4	7	3	0	5	8	4	7	5
	7	4	7	9	8	4	5	0	7	6	3	2
	8	1	8	4	1	1	8	7	0	9	4	8
	9	2	2	5	8	3	4	6	9	0	5	3
	10	9	3	6	5	3	7	3	4	5	0	5
	11	1	8	5	1	6	5	2	8	3	5	0

Table A4 Facilities and their corresponding index numbers in Case 2

Index Number	Facilities
1	Main gate
2	Side gate
3	Batching plant
4	Steel storage yard
5	Formwork storage yard
6	Bending yard
7	Cement and sand and aggregate storage yard
8	Curing yard
9	Refuse dumping area
10	Casting yard
11	Lifting yard

Table A5 Four types of materials and transport costs per unit distance in Case 2

Mk	Material	Cost Per Unit
1	aggregate, sand and cement/concrete	4
2	reinforcement bars	5
3	formwork	8
4	completed pre-cast units	8.5

Table A6 Coordinates of the available locations in Case 2

Location Number	1	2	3	4	5	6	7	8	9	10	11
X	15	13	22	25	20	12	40	48	48	5	32
Y	40	30	30	20	10	10	10	20	35	20	42

Table A7 Distance between locations for Case 2

Distance	Location	1	2	3	4	5	6	7	8	9	10	11
	1	0	12	17	30	35	33	55	53	38	30	19
	2	12	0	9	22	27	21	47	45	40	18	31
	3	17	9	0	13	22	30	38	36	31	27	22
	4	30	22	13	0	15	23	25	23	38	20	29
	5	35	27	22	15	0	8	20	38	53	25	44
Location	6	33	21	30	23	8	0	28	46	61	17	52
	7	55	47	38	25	20	28	0	18	33	45	40
	8	53	45	36	23	38	46	18	0	15	43	38
	9	38	40	31	38	53	61	33	15	0	58	23
	10	30	18	27	20	25	17	45	43	58	0	49
	11	19	31	22	29	44	52	40	38	23	49	0

Table A8 Flow frequency of the four types of materials between the facilities for Case 2

Facility	1	2	3	4	5	6	7	8	9	10	11
1. Aggregate, sand and cement											
1							20				
2							15				
3							35			35	
4											
5											
6											
7	20	15	35								
8											
9											
10			35								
11											
2. Reinforcement											
1				30							
2				20							
3											
4	30	20				50					
5											
6				50						50	
7											
8											
9											
10						50					
11											
3. Formwork											
1											
2											
3											
4											
5										48	
6											
7											
8											
9											
10					48						
11											
4. Complete pre-cast units											
1											28
2											20
3											
4											
5											
6											
7											
8										48	48
9											
10								48			
11	28	20						48			

Table A9 Site Facilities and their notes for Case 3

Index Name	Site Facilities
R1	Reinforcing steel shop 1
R2	Reinforcing steel shop 2
C1	Carpentry shop 1
C2	Carpentry shop 2
F1	Falsework shop 1
F2	Falsework shop 2
B1	Concrete batch plant 1
B2	Concrete batch plant 2
JO	Job office
LR	Labour residence
E	Electricity equipment and water-supply shop
W	Warehouse

Table A10 Construction Cost Matrix (C) for Case 3

Site Facilities	1	2	3	4	5	6	7	8	9	10	11	12
R1	35	35	30	30	35	15	10	15	6	6	7	10
R2	35	30	9	9	13	30	30	35	15	18	12	7
C1	18	15	15	15	15	8	14	10	8	10	15	15
C2	13	7	12	18	18	15	15	15	15	8	8	12
F1	18	15	15	20	15	8	10	8	8	7	15	15
F2	14	8	10	17	12	15	15	15	15	8	7	9
B1	32	35	15	15	15	10	9	13	7	10	15	15
B2	31	30	9	8	15	18	15	16	15	15	15	15
JO	39	35	13	8	8	15	18	15	8	18	9	18
LR	18	8	8	8	15	10	15	15	13	15	15	15
E	7	10	8	19	15	10	10	8	15	10	6	15
W	9	10	6	7	7	7	15	15	18	15	15	12

Table A11 Site Neighboring Index Matrix (A) for Case 3

	1	2	3	4	5	6	7	8	9	10	11	12
1	0	1	0	0	0	0	0	0	0	0	0	0
2	1	0	1	0	0	0	0	0	0	0	0	0
3	0	1	0	1	0	0	0	0	0	0	0	0
4	0	0	1	0	1	0	0	0	0	0	0	0
5	0	0	0	1	0	1	0	0	0	0	0	0
6	0	0	0	0	1	0	1	0	0	0	0	0
7	0	0	0	0	0	1	0	1	0	0	0	0
8	0	0	0	0	0	0	1	0	1	0	0	0
9	0	0	0	0	0	0	0	1	0	1	0	0
10	0	0	0	0	0	0	0	0	1	0	1	0
11	0	0	0	0	0	0	0	0	0	1	0	1
12	0	0	0	0	0	0	0	0	0	0	1	0

Table A12 Interactive Cost Matrix (D) for Case 3

	1	2	3	4	5	6	7	8	9	10	11	12
1	0	0	0	0	0	0	0	0	100	100	0	0
2	0	0	0	0	0	0	0	0	100	100	0	0
3	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0	0	0	0
9	100	100	0	0	0	0	0	0	0	0	0	0
10	100	100	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	0